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ECG SIGNALS FOR CHAOTIC DIAGNOSIS USING ANN, PSO AND WAVELET

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ABSTRACT

Today the main cause of human death is Cardiovascular disease (CVD). In order to combat this disease, many professionals are using mobile electrocardiogram (ECG) remote monitoring system. ECG Feature Extraction plays a significant role in diagnosing most of the cardiac diseases. In this paper a comprehensive review has been made for statistical feature extraction of ECG signal analyzing classifying method which have been proposed during the last decade and under evaluation that includes digital signal analysis, The present paper proposes a method of introducing Artificial Neural Network, To diagnose the condition of the heart Electrocardiography is an important tool but it is a time consuming process to analyze a long duration ECG signal as it may contain thousands of heart beats. This paper presents a new technique for customizing the wavelet functions adapted to the ECG signal pattern through the use of nonlinear dynamic principles. The performance of the proposed PSO model, along with the fixed set of free parameters, Hence it is desired to automate the entire process of heart beat classification and preferably diagnose it accurately. For subsequent analysis of ECG signals its fundamental features like amplitudes and intervals are required which determine the functioning of heart.

KEYWORDS: Artificial Neural Network, PSO, Discrete Wavelet Transform, ECG Signal, Non Stationary Chaotic Systems

INTRODUCTION

Electrocardiogram (ECG) is a nearly periodic signal that reflects the activity of the heart. A lot of information on the normal and pathological physiology of heart can be obtained from ECG. However, the ECG signals being non-stationary in nature, it is very difficult to visually analyze them. Thus the need is there for computer based methods for ECG signal Analysis.

The electrical activity is transmitted throughout the body and can be picked up on the skin which is the principle behind the ECG. An ECG machine records this activity via electrodes on the skin and displays it graphically. An ECG involves attaching 10 electrical cables to the body: one to each limb and six across the chest. ECG is a wave that represents an electrical event in the heart such as atria depolarization, ventricular depolarization, atria re-polarization, ventricular re-polarization. The signal consists of a series of repetitive complex waveforms with a frequency of approximately 1 Hz. One cardiac cycle in an ECG signal consists of the P-QRS-T waves. Conventional methods of monitoring and diagnosing electrocardiographic changes rely on detecting the presence of particular signal features by a human observer [2].

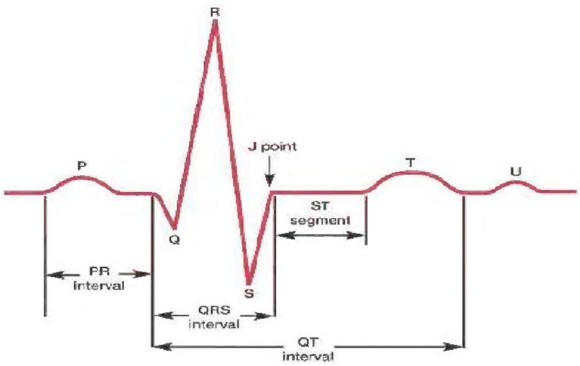

Figure 1: ECG Signal Showing P-QRS-T Wave

QRS complex is the most prominent feature in electrocardiogram because of its shape; therefore it is taken as a reference in ECG feature extraction. Computer based medical diagnostic systems have been developed in order to assist medical professionals in the analysis of large volumes of patient data. Such techniques work by transforming the mostly qualitative diagnostic criteria into a more objective quantitative signal feature classification problem [2]. The techniques have been used to address this problem such as the analysis of ECG signals for detection of electrocardiographic changes using the autocorrelation function, frequency domain features, time-frequency analysis, and wavelet transform. Some methods consist of series of band pass filters having frequency range of QRS complexes but these methods have limited accuracy in analyzing ECG features in presence of high frequency noise as well as the ECG signal affected by severe base line drift [3].Various techniques proposed earlier in literature for extracting the features from ECG is analyzed this paper discusses and a review has been made to find out the best among them with less computational complexity and more accuracy in prediction and feature extraction.

SYSTEM DESIGN MODEL

Analysis of ECG for Diagnosis

Feature extraction method using wavelet transform and classification using support vector machines was first proposed in [1]. A new approach to the feature extraction was presented for reliable heart recognition. Three main steps were performed-

- Data preprocessing,
- Feature extraction and
- Classification of ECG signals.

Two methods were applied together to extract the features of ECG signal which gives the feature vector of ECG data set. To extract the coefficients of the transform as the features of each ECG segment wavelet transform is used. Concurrently, autoregressive modeling (AR) is also applied to get hold of the temporal structures of ECG waveforms. Then finally the support vector machine (SVM) with Gaussian kernel is used to classify different ECG heart rhythm. The results of computer simulations reached the overall accuracy of 99.68%.

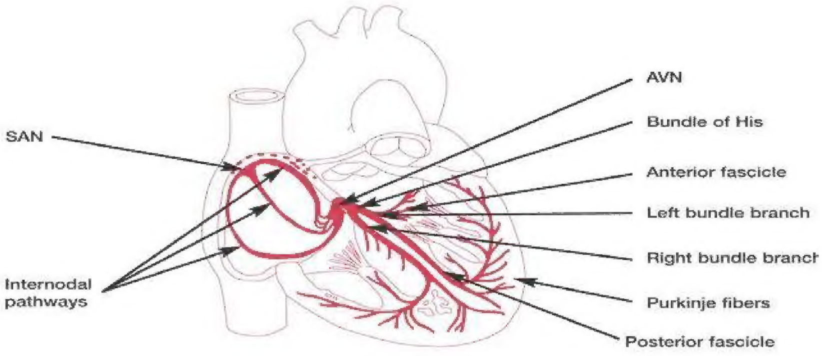

Figure 2: Cardiac Depolarization Root [3]

The cardiac depolarization rout has been shown in figure 2. The wave of depolarization then proceeds rapidly to the bundle of His where it splits into two pathways and travels along the right and left bundle branches [3]. The impulse travels the length of the bundles along the interventricular septum to the base of the heart, where the bundles divide into the Purkinje system [3]. The wave of depolarization is then distributed to the ventricular walls and initiates ventricular contraction. The first step in extracting ECG features starts from the accurate detection of R peaks in the QRS complex.

A robust R wave detector using the wavelets was developed [2] by Awadesh and Manabendra. The database has been collected from MIT-BIH arrhythmia database and the signals from Lead-II have been analyzed. The selection of detail coefficient d4 has been done based on the following important parameters i.e.

- Energy
- Frequency and
- Cross-correlation analysis

of decomposition structure of ECG signal. Forty two records were tested for R peaks. The overall of detection using Daubechies (db6) and Symlets (sym11) family of wavelets are 96.65% and 84.37% respectively. The importance of using wavelet transform has been highlighted in which the noise is filtered at each level of decomposition thus eliminating the requirement of any preprocessing. This ensures the robustness of the method. Further confirmation is done using different records of the database with noise present in it. The results with db6 have been found to be more stable by varying threshold than sym11 which picks up false peaks (missed peaks) [4]. The summation of the values from these segments provided the feature vectors of single cycles. This algorithm was tested on two ECG signals, the first was taken from the MIT biomedical database was decomposed into four levels and de-noised by the optimal wavelet "sym4" with global threshold value 1.3073. This ECG signal was with local abnormal heartbeat activity [5]. The second ECG signal was recorded from a patient during an epileptic seizure. The optimal wavelet function was wavelet Coiflet5 "coif5" with global threshold 23.217. The three waves of the QRS complex represent ventricular depolarization [3].

- Small Q waves correspond to depolarization of the interventricular septum. Q waves can also relate to breathing and are generally small and thin. They can also signal an old myocardial infarction (in which case they are big and wide)
- The R wave reflects depolarization of the main mass of the ventricles –hence it is the largest wave
- The S wave signifies the final depolarization of the ventricles, at the base of the heart

Artificial Neural Network Based Data Processing for PSO

The introduced ANN was trained by the main features of the 63 ECG images of different diseases. In particle swarm optimization a group of particles, referred to as the population or potential solutions, is flown in a multidimensional search space to determine the optimum position of them. This optimum position is usually characterized by the optimum of a fitness function. The test results showed that the classification accuracy of the introduced classifier was up to 92%. The extracted features of the ECG signal using wavelet decomposition was effectively utilized by ANN in producing the classification accuracy of 92%.

Another algorithm for feature extraction of ECG signals was proposed by in [7]. The basic focus of the work was to evaluate the classification performance of an automatic classifier of the electrocardiogram (ECG) for the detection of abnormal beats. The concept of feature extraction was completely new. The obtained feature sets were based on ECG morphology and RR-intervals. Configuration adopted Kohonen self-organizing maps (SOM) for examination of signal features and clustering. A classifier was developed with SOM and learning vector quantization (LVQ) algorithms using the data from the records recommended by ANSI/AAMI EC57 standard.

The ECG signals (normal beat, congestive heart failure beat, ventricular tachyarrhythmia beat, a trial fibrillation beat) from the Physio-bank database were used for training and testing of classifiers. MME classifier trained on the three diverse feature vectors produce better performance than that of the ME trained on the composite features. The results of the present study demonstrated that the MME can be used in classification of the ECG signals by taking into consideration the misclassification rates.

Sufi et al [8] formulated a new ECG obfuscation method for feature extraction and corruption detection. A new ECG obfuscation method was presented, which uses cross correlation based template matching approach to distinguish all ECG features followed by corruption of those features with added noises. Reconstruction of the obfuscated features was difficult without the prior knowledge of the templates used for feature matching and the noise. Therefore, three templates and three noises were considered for P wave, QRS Complex and T wave comprise the key, which is only 0.4%-0.9% of the original ECG file size. With this obfuscation model, the corrupted ECG appears as regular ECG without encryption, noise can be represented in enormous number of combinations establishing unmatched security and the key distribution is efficient due to its small size.

In [9] an approach for effective feature extraction from ECG signals was described. This research work deals with a composite method which has been developed for

- Data Compression
- Signal retrieval &
- Feature extraction of ECG signals.

This traditional PSO model showed quick, aggressive movement narrowing down towards the solution region but often encountered problem in fine tuning the search to determine the supreme solution. Since then two important modifications of PSO attempted to rectify this problem by introducing a judicious mix of aggressive, coarse updating during early iterations and relaxed, fine updating during later iterations. It has been found that signal retrieval from the compressed data not only compresses the data but also improves the quality of the retrieved ECG signal with respect to

elimination of high-frequency interference present in the original signal. The best topology with two hidden layers and four elements in each hidden layer has been finalized for ECG data compression using a Military Hospital (MH) data base. It has been observed that a higher compression ratio can be achieved using ANN, as compared with other methods of data compression, because the compression ratio in this method depends on the number of cycles taken for compression. Moreover the features extracted by amplitude, slope and duration criteria from the retrieved signal match with the features of the original signal. Their experimental results at every stage are steady and consistent and prove beyond doubt that the composite method can be used for efficient data management and feature extraction of ECG signals in many real-time applications.

Wavelet Analysis of ECG Signals

ECG signals are gathered and stored in analytical instruments (e.g., ECG machines) in the form of time-series. They can be transformed from the time domain into frequency, time-frequency, or other domains depending on the nature of the information required. The wavelet representation can be useful for interrogating the spectral component prevailing at a given time instant. A feature extraction method using Discrete Wavelet Transform (DWT) was proposed in [10]. It used a discrete wavelet transform (DWT) to extract the relevant information from the ECG input data in order to perform the classification task. The proposed work includes the following modules.

- Data acquisition,
- Pre-processing beat detection,
- Feature extraction and
- Classification.

In the feature extraction module the Wavelet Transform (DWT) is designed to address the problem of non-stationary ECG signals. It was derived from a single generating function called the mother wavelet by translation and dilation operations. Using DWT in feature extraction may lead to an optimal frequency resolution in all frequency ranges as it has a varying window size, broad at lower frequencies, and narrow at higher frequencies. The DWT characterization will deliver the stable features to the morphology variations of the ECG waveforms.

The nonlinearity of ECG signal was considered in this letter and chaos theory was put forward to study the behavior of dynamical system from an experimental time series (ECG Signal) [11]. To reduce the dimensionality of the extracted features statistical features were used. The results confirmed that the MLPNN trained with the Leven berg– Marquardt algorithm has potential in detecting the variability of the ECG signals. Total classification accuracy is 95%.

In [12] an algorithm was proposed based on chaos theory for ECG feature extraction. Numerous chaos methods, including phase space and attractors, correlation dimension, spatial filling index, central tendency measure and approximate entropy were discussed. A new feature extraction environment was created called ECG chaos extractor to apply the above mentioned chaos methods. A new semi-automatic program for ECG feature extraction has been implemented and is presented in this article. Graphical interface is used to specify ECG files employed in the extraction procedure as well as for method selection and results saving. The program extracts features from ECG files.

Local Recurrence Prediction in Nonstationary Chaotic Systems

A local recurrence modeling approach for state andperformance predictions in complex nonlinear and non-stationary systems. Non-stationary is treated as the switching force between different stationary systems, which is shown as a series of finite time detours of system dynamics from the vicinity ofan attractor of a nonlinear process. Recurrence characteristics of the attractor are used topartition the system trajectory into multiple near-stationary segments. Consequently, piece-wise eigen analysis of ensembles in each near-stationary segment can capture bothnonlinear stochastic dynamics and non-stationarities. Extensive studies using simulatedand real world datasets reveal significant prediction accuracy improvements over otheralternative methods.

The present approach exploits the inherent nonlinear stochastic dynamics ofcomplex manufacturing systems to improve predictive capability under noisy and non stationary conditions. Here, non-stationarity includes not just simple drifts in variousstatistical moments over time, but also intermittent low and high dimensional chaoticbehaviors resulting from the random fluctuations of the model parameters. Central to ourapproach is the segmentation of global performance signature (time-series) into multiplestationary segments using recurrence analysis. Stationary segmentation will lead toreduced order models that can capture the local evolution patterns (including the complexity and non-stationarities) better than any global model.

SIMULATION RESULTS

Figure 3 contains ECG signal tracetaken from a subject with AF for the duration of approximately 10 heartbeats. The traceshows a QRS complex with a significant R-peak followed by a T-wave. The signal is superposed with higher frequency (>6Hz) atrial fibrillation P-waves in lieu of P-waves. After the false nearest neighbor and mutual information test, the optimal embedding dimension and time delay were determined for reconstruction of the state space from the ECG traces using time delay.

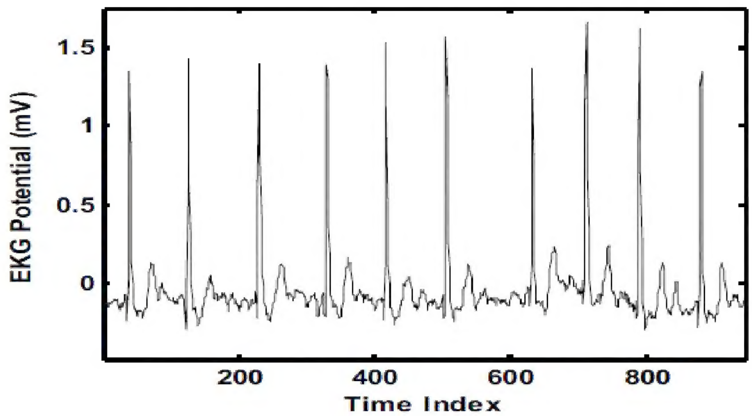

Figure 3: Time Domain Plot of a Representative ECG Signal Trace

Figure 3 shows the least square matching wavelet design result. The resulting wavelet ψ (t) holds significant similarities to the fiducial pattern ψ'(t) and capture a majority of the variations among the ensembles.

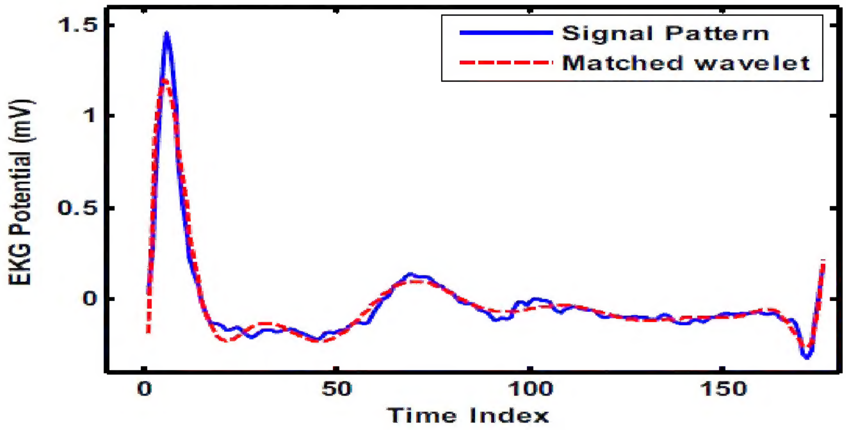

Figure 4: Matching Wavelet Extracted from Fiducial Signal Pattern

The two orders of magnitude increase in the compactness of ECG signal representation with customized wavelet (measured in terms of entropy reduction) is further evidenced from the examination of the distribution of entropies for eleven signals (a01, a02, a03, b01, b02, n01, n02, s01, s02, t01, t02) in the Physio Net database for the AF challenge with the eleven alternative wavelet bases including the standard and the customized wavelets (see Figure 5). Interestingly, the wavelets customized for an ECG signal from a normal case yield about five times lower entropy compared to that from a non-terminating AF case. Also, it may be noted that, although the customization yield ignorantly low entropy compared to standard wavelet basis.

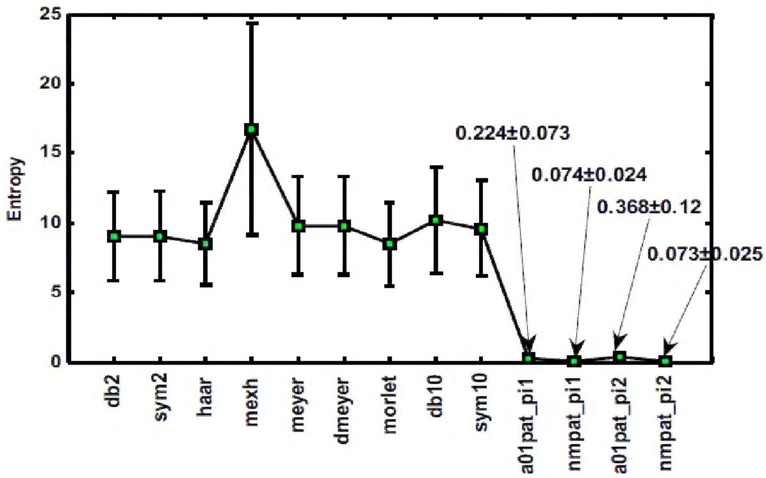

Figure 5: Entropy Distribution for Different Wavelet Representations, Taken over All ECG Signals in the Database Considered

The present work is one of the first attempts to use recurrence analysis forprediction in the presence of generic forms of nonstationarities. It combines the principlesof statistical estimation with dynamic systems theory.

The following two scenarios are simulated towards evaluating the local recurrencemodeling approach: (1) nonlinear and stationary signals generated by contaminating thefirst component of Lorenz attractor [9] with three different noise levels (signal noiseratios (SNR) between 7.37dB-21.35dB); (2) nonlinear and nonstationary signals obtainedby dividing the contaminated Lorenz time series into several segments and randomlyrearranging the sequence of these segments (SNR varied between 7.37dB-21.35dB).

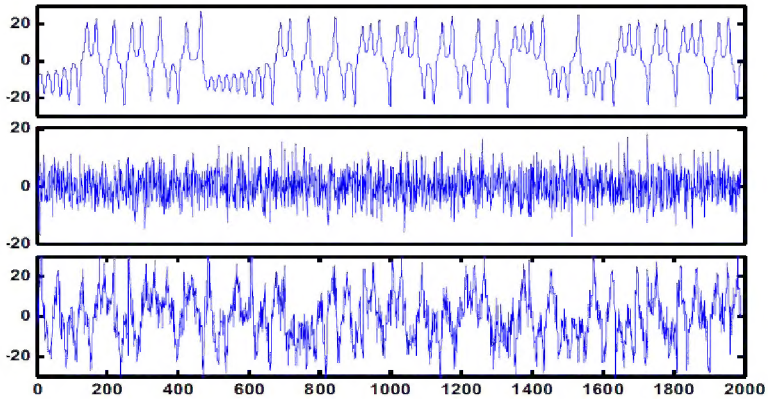

Figure 6: Top Original Lorenz Time Series, Middle – Random Gaussian Noise, Bottom– Random Permutated Lorenz Time Series Contaminated by Noise

CONCLUSIONS

This paper provides an overview of the various techniques and algorithms for feature extraction of ECG signal proposed earlier in literature. The feature extraction technique or algorithm developed for ECG must be highly accurate and should ensure fast extraction of features from the ECG signal. In general, the closer the basis function captures the signal characteristics, the more compact is the representation, and more likely are the features sensitive to relevant ECG states and insensitive to variations in extraneous noise. In this chapter, we have customized the basic functions of a continuous wavelet representation by choosing polynomial wavelet basis functions that match the characteristics of a fiducially 1-beat long ECG signal pattern extracted from the Poincare sectioning of ECG state space. The customized representations were found to be roughly two orders of magnitude more compact (measured in term of signal entropy) than the wavelet basis functions available in the standard wavelet library.

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